Mitigating the risks of deregulation:
The role of supervisory attention

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Abstract

We study how regulation and supervision interact to affect bank risk. Exploiting the 2018-2019 U.S. bank deregulation, we show that mid-sized banks subject to relaxed liquidity requirements experienced a deterioration in liquidity. At the same time, using confidential data from the Federal Reserve on supervisory hours, we document that these banks were subject to more intense supervision, with in an increase in examination activity. Our evidence suggests that the increase in supervisory intensity mitigates the liquidity deterioration. These effects are stronger in districts where supervisors oversee fewer banks and have longer tenure. These results underscore the complementary roles of regulation and supervision, and suggest that preserving supervisory capacity can enhance the resilience of the banking system.

JEL classification: G21, G28, G01

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> “The whole point of supervision is to fill in the many blanks that are left by quantitative metrics,” he said. “If your regulations on capital are less restrictive, then you should be more focused on making sure that any shift in bank activities is not creating problems.”
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> Daniel K. Tarullo, former Governor of the Federal Reserve Board, quoted in “The Fed is Cutting Bank Oversight. Critics See Risks” *New York Times*, 17 November 2025

1 Introduction

Regulation and supervision of banks are central topics in the study of financial stability. While the effects of regulatory changes on bank behavior have been widely examined, less attention has been devoted to the role of supervision – the enforcement and interpretation of existing rules – in shaping bank risk (Hirtle and Kovner 2022). This distinction has gained prominence in the aftermath of the 2023 U.S. banking crisis, which prompted concerns that deficiencies in both regulation and supervision contributed to the observed instability (Barr 2023). These concerns have become more salient following announcements of staff cuts by the Federal Reserve (10% of general staff and 30% of bank supervisory staff) and the FDIC (18%), raising important questions about the capacity to maintain effective oversight in a constrained environment.[1] In this paper, we ask whether deregulation is associated with an increase in bank risk, and whether supervision can mitigate this effect.

We show that U.S. bank holding companies (BHC) whose liquidity requirement was relaxed by the 2018 Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA) and the subsequent 2019 “tailoring rule” exhibit deteriorating liquidity. Moreover, using confidential administrative data on the number of hours spent by Federal Reserve System employees in supervision tasks, we find that the liquidity deterioration is attenuated for banks that receive more supervision. These findings are consistent with supervision acting as a tool that can help stabilize the banking system when regulation is laxer.

Studying the role and systemic implications of regulation and supervision confronts us with

[1] “Federal Reserve Will Cut Staff by 10%” *Forbes*, 16 May 2025; “Federal Reserve to Reduce Bank Supervision Staff by 30%” *Wall Street Journal*, 30 October 2025; “FDIC Hunts Extra 20% Staff Cut as DOGE Descends on Agency” *Bloomberg*, 11 April 2025.

empirical and data challenges. First, it is difficult to disentangle the impact of regulation from that of supervision, because banks that are subject to stricter regulation are typically the larger, more systemic ones that are also exposed to more stringent supervision. As a result, a test might incorrectly impute to regulation the effects of supervision and vice-versa. Second, the intensity of supervision is not random, as riskier banks will endogenously receive more attention from their supervisors. This form of assortative matching might induce a spurious positive relation between supervision and risk. Third, measuring supervision itself is not trivial, as the researcher does not typically observe supervisory tasks directly and how much effort supervisors devote to them.

We exploit our data and our test setting to address these challenges. First, we exploit a regulatory change that relaxed specific aspects of regulation for a specific set of U.S. banks. The EGRRCPA, passed by Congress on 24 May 2018, opened the way to relax liquidity requirements for mid-sized banks. In October 2019, the Federal Reserve approved the so-called "tailoring rule", which implemented the EGRRCPA restricting the definition of mid-sized banks to bank holding companies with total assets between \$100 bn and \$250 bn, subjecting them to relaxed Liquidity Coverage Ratio (LCR) requirements.[2] Second, we address the potential endogeneity of supervision and assortative matching between supervisory attention and bank risk with an identification approach based on the unique institutional features of the Federal Reserve's supervisory environment (Hirtle, Kovner, and Plosser 2020). We exploit the fact that supervision is organized by individual Fed districts, whose boundaries were defined in the early 1900s and are essentially unrelated to the modern-day bank risk; the largest banks in each district will receive more supervisory attention, so that (say) the largest bank in the 6th (Atlanta) district other things equal receives more supervisory hours than a comparable bank in the 2nd (New York) district. The within-district size ranking of bank holding companies thus provides us with an instrument for supervisory attention. Third, we address the data challenge and measure supervisory attention itself using confidential, administrative data maintained by the Federal Reserve Board. The data report the hours spent by employees of the Federal Reserve System in supervisory tasks, providing us with a comparatively

[2]We discuss the details of the EGRRCPA and the tailoring rule in Section 2.A.

precise measure of supervision dedicated to each bank.

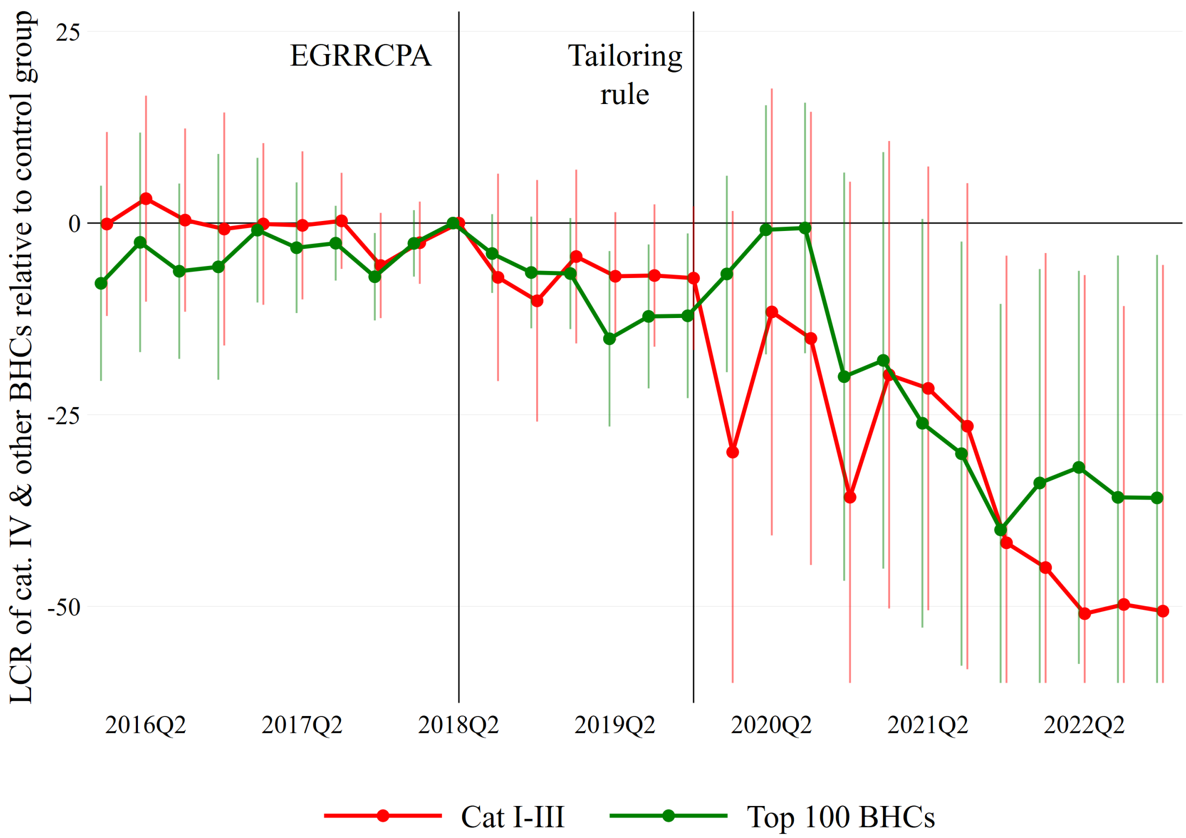

Figure 1. Liquidity deterioration at the "Category IV" and "other" banks
The figure illustrates the estimates of $LCR_{it} = \sum_t \gamma_t CatIV\&Other_i \times \mathbb{1}_t + \ln(1 + Fiscal\ Stimulus_{it}) + \varepsilon_{it}$, where $CatIV\&Other_i$ denotes an indicator equal to 1 for bank holding companies placed in the "Category IV" and "other banks" group in the 2019 tailoring rule, $\mathbb{1}_t$ denotes indicators for each calendar quarter over the period from 2016Q1 to 2022Q4 (the omitted indicator is 2018Q2, corresponding to the passage of the EGRRCPA), and $Fiscal\ Stimulus$ denotes deposits flowing into the bank holding company attributable to the COVID-19 stimulus (defined in detail in Appendix D). It shows that, relative to two alternative benchmarks (Category I, II, and III banks and other top-100 U.S. bank holding companies), liquidity deteriorates for the "Category IV" and "other banks".

We structure our analysis around the liquidity of the set of mid-sized bank holding companies whose liquidity requirements are relaxed following the EGRRCPA and the tailoring rule, denoted in the tailoring rule as "Category IV" banks (total assets in the \$100-\$250bn range) and "other" banks (total assets in the \$50-\$100bn range), over the period 2016Q1-2022Q4. We find that the Category IV and other banks exhibit deteriorating liquidity in the aftermath of the relaxation of the regulation. This is immediately visible in Figure 1, where their LCR drops by over 30 percentage points relative to two alternative benchmark groups: the top 100 largest bank holding companies in the U.S.; and the Category I, II, and III banks, with total assets above $250bn, which are subject to stricter liquidity/LCR requirements throughout the same period. The visual intuition from Figure 1 is confirmed by formal statistical tests; it is robust to the inclusion of control variables; and it is not driven by the COVID recovery stimulus enacted by the first Trump and Biden administrations. These results are consistent with the notion that banks facing a laxer liquidity regulation exhibit deteriorating liquidity in the aftermath of the passage of the EGRRCPA and the issuance of the tailoring rule.

Next, we turn to the role of supervision. First, we examine how supervisory resources were reallocated following the EGRRCPA for the banks most directly affected by the regulatory change. For Category IV and other banks, we find evidence of an increase in overall supervisory intensity, where total supervisory hours rise, albeit only modestly. More importantly, the composition of supervision shifts markedly. Examination activities account for a larger share of total supervisory effort, reflecting both an increase in examination hours and a simultaneous decline in continuous monitoring, i.e., ongoing supervisory engagement with bank management outside of formal examinations. Taken together, these patterns are consistent with supervisors rebalancing their attention towards more discrete, exam-based oversight, rather than expanding supervisory resources for deregulated banks.

Second, we relate supervisory hours to liquidity risk at Category IV and other banks. Because supervisory intensity may respond endogenously to risk, simple correlations may reflect assortative matching, with riskier banks receiving more supervisory attention. To address this possibility, we follow Hirtle, Kovner, and Plosser (2020) and use as an instrument for supervisory hours the Top-5-plus indicator, which identifies the largest banks in each Federal Reserve district and nearby-in-size peers that tend to receive disproportionately high supervisory attention. We find that, among Category IV and other banks, higher supervisory intensity is associated with a more muted deterioration in liquidity risk. Banks exposed to lower supervisory intensity experience a substantially larger decline in their liquidity coverage ratios, with economically meaningful differences by the end of the sample period. The evidence is consistent with the view that, in an environment of laxer regulation, more intensive supervision plays an important role in containing liquidity risk.

Finally, we shed light on the mechanisms through which supervision mitigates liquidity risk, by exploiting heterogeneity in supervisory capacity and experience. First, we find that the attenuating effect of supervisory hours is concentrated in Federal Reserve districts with greater supervisory capacity – measured by the number of supervisory staff relative to the number of bank holding companies overseen – while it is largely absent in districts where supervisory resources are more constrained. This pattern is consistent with capacity constraints limiting supervisors' ability to translate oversight into effective risk mitigation. Second, we examine the role of supervisory tenure. Supervisory hours associated with longer-tenured supervisors are linked to a stronger attenuation of liquidity risk, whereas hours associated with shorter-tenured supervisors exhibit weaker and statistically less precise effects. Taken together, these results suggest that both the availability of supervisory resources and the institutional continuity of supervision shape its effectiveness in constraining bank risk.

Related literature. Our paper makes three main contributions to the literature. First, it contributes to the literature on banking supervision, which studies how supervisory oversight affects bank behavior, lending practices, and broader economic outcomes. Work in this area has focused on the institutional design of supervision, showing how supervisory intensity and accountability influence risk-taking and compliance (Agarwal, Lucca, Seru, and Trebbi 2014, Hirtle, Kovner, and Plosser 2020), and on the causal effects of supervisory interventions, such as on-site inspections and stress tests, on lending and credit allocation (Bonfim, Cerqueiro, Degryse, and Ongena 2022, Correia, Luck, and Verner 2025, Eisenbach, Lucca, and Townsend 2022, Passalacqua, Angelini, Lotti, and Soggia 2020, Granja and Leuz 2024, Gopalan and Granja 2024, Agarwal, Morais, Seru, and Shue 2024, Beyhaghi, Chae, Curti, and Gerlach 2026). We contribute to this literature by using confidential data on examiner hours to quantify supervisory intensity, and by providing causal evidence that greater supervisory attention can mitigate the increase in liquidity and market-based risk triggered by a deregulatory shock. Our identification strategy, based on institutional drivers of the supervisors' attention allocation within Fed districts, allows us to isolate the effect of supervision and adds to our understanding of how supervisory capacity shapes financial stability.

Second, our paper contributes to the literature on bank liquidity regulation, which examines how liquidity requirements influence banks' balance sheet composition and risk-taking. Prior work shows that rules like the Liquidity Coverage Ratio (LCR) increase liquid asset holdings (Hong, Huang, and Wu 2014, Sundaresan and Xiao 2024) but can also lead to greater exposure to liquidity risk or risk-shifting (Acharya, Chauhan, Rajan, and Steffen 2023, Bosshardt, Kakhbod, and Saidi 2024). Liability-side frictions have received growing attention, with Koont, Santos, and Zingales (2023) highlighting the role of deposit stickiness and Bosshardt, Kakhbod, and Saidi (2024) documenting that stable funding can amplify banks' responses to regulation. We contribute by showing that supervision can temper the risk-enhancing effects of deregulation. Using confidential data on examiner hours and quasi-random variation in supervisory hours, we find that more intensively supervised banks reduce liquidity risk following deregulation – suggesting that supervision complements regulation by shaping how banks adjust to changing liquidity requirements.

Third, our paper also contributes to the recent literature on the 2023 U.S. banking turmoil, which has highlighted the fragility of banks with large unrealized losses and substantial reliance on uninsured deposits (Jiang, Matvos, Piskorski, and Seru 2024, Dursun-de Neef, Ongena, and Schandlbauer 2023, DeMarzo, Jiang, Krishnamurthy, Matvos, Piskorski, and Seru 2023). This literature has emphasized different mechanisms, including interest rate risk (Granja, Jiang, Matvos, Piskorski, and Seru 2024, Greenwald, Krainer, and Paul 2024, Cipriani, Eisenbach, and Kovner 2024, Fuster, Paligorova, and Vickery 2024), capital fragility (Flannery and Sorescu 2023), and the amplification of run risk through digital communication (Cookson, Fox, Gil-Bazo, Imbet, and Schiller 2026). While our focus is not on the crisis per se, our findings complement these studies by examining the role of supervision in shaping banks' liquidity resilience ex ante.

2 Institutional background

A The EGRRCPA and the tailoring rule

During his 2016 presidential campaign, Donald Trump emphasized the objective of reducing regulatory burdens, particularly those imposed by the Dodd-Frank Act (2010), originally enacted in response to the global financial crisis of 2008. Trump frequently criticized the Dodd-Frank Act for being overly burdensome, particularly on smaller banks, and argued that it limited credit and economic growth. As a result, rolling back parts of the Dodd-Frank Act was a key component of Trump's 2016 platform, focusing on relaxing the application of Dodd-Frank's measures based on banks' size and risk profile.[3]

The Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA) was signed into law on May 24, 2018 with broad support.[4] The EGRRCPA amended the Dodd-Frank Act in several parts, making targeted changes to the regulatory framework, specifically around the thresholds and tailoring. We focus specifically on the changes made to Section 165 of Dodd-Frank, which raised the total assets threshold for automatic application of enhanced prudential standards (EPS). Pre-EGRRCPA, banks with total assets above $50bn were subject to enhanced prudential standards including Liquidity Coverage Ratio (LCR), stress tests, and risk management requirements; post-EGRRCPA, the threshold was raised to $250bn, although the Federal Reserve retained discretion to apply stricter standards to banks with total assets in the $100-$250bn range.

To implement the EGRRCPA, the Federal Reserve, together with the Federal Deposit Insurance Corporation (FDIC) and the Office of the Comptroller of the Currency (OCC), adoped a "tailoring

[3]Trump argued that the Dodd-Frank Act made it "impossible for bankers to function" and that its provisions made it "very hard for bankers to loan money for people to create jobs, for people with businesses to create jobs" ("Trump preparing to dismantle Obama's Wall Street reform law." *Reuters*, 18 May 2016). In the aftermath of the 2016 election, Trump's transition team reiterated this stance, stating that the new administration would replace Dodd-Frank with policies aimed at encouraging economic growth ("Trump's transition team pledges to dismantle Dodd-Frank Act." *Bloomberg*, 10 November 2016). Reflecting Trump's position, the 2016 Republican Party platform explicitly called for the repeal of Dodd-Frank ("8 questions about the future of banking regulation under Trump." *Washington Post*, 23 November 2016).

[4]The EGRRCPA passed in the Senate on 14 March 2018 by a vote of 67 to 31 (all Republican senators and 17 out of 47 Democrat senators voted in favor); it passed in the House of Representatives on 22 May 2018 by a vote of 258 to 159 (all but one Republican representatives and 33 out of 193 Democrat representatives voted in favor).

rule" in October 2019. Prior to the EGRRCPA and the tailoring rule, LCR requirements in the U.S. were primarily based on the 2014 LCR rule issued by U.S. banking regulators, which implemented the Basel III liquidity standards. The 2014 rule divided banks into three tiers: (i) Full (100% daily) LCR requirement applying to banks with at least $250bn in total assets or $10bn in on-balance-sheet foreign exposure; and (ii) Modified (70% monthly) LCR requirement for banks with between $50bn and $250bn total assets and less than $10bn in foreign exposure; and (iii) No LCR requirement for banks under $50bn total assets.

The tailoring rule introduces a risk-based tiering of enhanced prudential standards for large and mid-sized bank holding companies, distinguishing four categories. Category I firms (U.S. GSIBs) are subject to the full set of enhanced prudential standards. Category II firms (with at least $700bn in total assets or $75bn in cross-jurisdictional activity) and Category III firms (with at least $250bn in total assets or at least $75bn in weighted short-term wholesale funding, non-bank assets, or off-balance-sheet exposure) are subject to progressively reduced standards. Category IV firms, with $100-$250bn in total assets that do not meet the Category III risk thresholds, are subject to the lightest enhanced prudential standards, including biennial stress tests and tailored liquidity requirements. Specifically, for Category IV firms the application of the Liquidity Coverage Ratio depends on their reliance on short-term wholesale funding: firms with sufficiently high short-term wholesale funding remain subject to a modified (70%, monthly) LCR requirement, while firms below the threshold are not subject to a standardized LCR. Bank holding companies with total assets between $50bn and $100bn ("other" banks) are not subject to the LCR under the tailoring framework.

We therefore focus our analysis on Category IV and other banks, and in particular on their liquidity, as this is the dimension of regulation that changed most sharply following the EGRRCPA and the 2019 tailoring rule. For these institutions, the tailoring framework relaxed quantitative liquidity requirements relative to the pre-EGRRCPA regime by making the application of the Liquidity Coverage Ratio conditional on banks' reliance on short-term wholesale funding, and by eliminating standardized LCR requirements altogether for other banks with $50-$100bn in assets. At the same time, both Category IV and other banks remain subject to risk-based capital requirements, and Category IV banks continue to face supervisory stress tests, albeit on a biennial cycle. This institutional setting isolates liquidity regulation as the primary margin of regulatory adjustment for mid-sized banks, making it a natural focus for studying the interaction between deregulation and supervisory oversight. Moreover, as discussed below, liquidity risk played a central role in the 2023 U.S. banking crisis, underscoring the relevance of this dimension for financial stability and bank supervision.

B The 2023 U.S. banking crisis

In March 2023, several U.S. regional banks failed, most prominently Silicon Valley Bank (SVB), triggering a broader banking crisis that also included the failures of Signature Bank and First Republic Bank and propagated internationally with the collapse of Credit Suisse. The episode exposed vulnerabilities of the U.S. banking system related to liquidity risk and exposure to long-term interest rate movements, as well as weaknesses in the system of tailored regulation introduced in 2019, which relaxed quantitative liquidity requirements for Category IV and other mid-sized banks.

SVB exhibited a fragile liquidity profile, characterized by a heavy reliance on large, uninsured, and highly concentrated corporate deposits. Although its total assets exceeded \$200bn by 2023, SVB was not subject to a standardized Liquidity Coverage Ratio under the post-EGRRCPA regulatory framework. Under the 2019 tailoring rule, Category IV status does not automatically trigger an LCR requirement: the application of a modified (70%, monthly) LCR depends on whether a bank exceeds specified thresholds for short-term wholesale funding. SVB's funding model, while risky, relied primarily on deposits and did not meet these thresholds, and the formal application of enhanced liquidity requirements was further delayed by the timing and implementation of regulatory classifications. Estimates suggest that SVB's LCR would have been approximately 75%, substantially lower than the liquidity typically held by large U.S. and global banks, rendering it vulnerable once unrealized losses on long-duration securities became salient to depositors and withdrawals accelerated (Feldberg 2023, Jiang et al. 2024).

On 10 March 2023, SVB was closed by the California Department of Financial Protection and Innovation and placed into FDIC receivership, marking the second-largest bank failure in U.S. history at the time. Two days later, Signature Bank was closed by New York regulators, and U.S. authorities invoked a systemic risk exception to guarantee all uninsured deposits at both institutions. The crisis subsequently spread to First Republic Bank, which was seized and sold to JPMorgan Chase on 1 May 2023, and to Europe, where Credit Suisse was acquired by UBS on 19 March 2023 with government support.

Importantly, the failure of SVB was not solely the result of regulatory design. Although supervisors retained discretion under the tailoring framework to impose stricter liquidity standards based on a bank's risk profile, this discretion was not exercised. An internal review by the Federal Reserve Board of Governors concludes that supervisory oversight failed to translate identified risks – most notably depositor concentration and exposure to rising interest rates – into timely and decisive supervisory action (Barr 2023).

More broadly, Jiang et al. (2024) show that many U.S. banks shared similar liquidity mismatch risks prior to the crisis, holding large unrealized losses on long-duration assets while relying on short-maturity, uninsured deposits. These features imply that the banking system may be broadly vulnerable to runs when uninsured depositors move quickly. In this context, regulatory gaps in the treatment of liquidity and interest rate risk, combined with insufficiently forward-looking supervision, emerge as central contributors to financial fragility. In response to the crisis, policy proposals have focused on revising the tailoring framework, potentially lowering thresholds for enhanced prudential standards, strengthening or redesigning the LCR to better reflect asset maturity and marketability, and improving the integration of liquidity and interest rate risk supervision (Acharya, Carletti, Restoy, and Vives 2024, Baer 2023).

C Federal Reserve supervision

The Federal Reserve supervises bank holding companies and state member banks in the United States with the objective of promoting the safety and soundness of supervised institutions and, more broadly, the stability of the financial system. Supervision is distinct from regulation. While regulation specifies the rules and quantitative requirements under which banks operate, supervision involves the ongoing monitoring and assessment of banks' risk profiles, governance, and risk-management practices, as well as the imposition of institution-specific remedial actions when deficiencies are identified (Federal Reserve Board 2023c, Hirtle and Kovner 2022).

Federal Reserve supervision relies on two broad categories of activities: formal supervisory examinations and continuous monitoring. Formal examinations are structured, in-depth reviews of a bank's activities and financial condition. These examinations typically involve on-site or targeted reviews of capital adequacy, asset quality, earnings, liquidity, and risk-management practices, and result in written supervisory assessments communicated to bank management (Federal Reserve Board 2023b). A central role of examinations is the acquisition of quantitative and qualitative supervisory information needed to evaluate a bank's safety and soundness and to determine whether corrective actions are warranted (Hirtle and Kovner 2022).

Supervisory examinations can be conducted at either the consolidated bank holding company level or the individual bank level. At the holding company level, the Federal Reserve's supervisory rating frameworks have evolved over time. From 1979 through 2004, holding companies were evaluated using the BOPEC rating system. In 2005, BOPEC was replaced by the RFI/C(D) framework, which emphasizes risk management (R), financial condition (F), and the potential impact (I) of nonbank activities on depository institutions, along with a composite rating. In 2018, the Federal Reserve introduced the Large Financial Institution (LFI) rating system for the largest and most complex firms, focusing on firm-wide capital, liquidity, and governance and controls (Hirtle and Kovner 2022). At the individual bank level, supervisors assign CAMELS ratings, which summarize examiners' assessments of a bank's Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity to market risk. These ratings reflect informed supervisory judgment rather than a mechanical aggregation of component measures (Hirtle and Kovner 2022).

In addition to formal examinations, supervisors engage in continuous monitoring of supervised institutions. Continuous monitoring encompasses supervisory activities conducted outside of scheduled examinations, including regular meetings with bank management, review of internal bank data, audit reports, and regulatory filings, and coordination with other regulatory agencies (Federal Reserve Board 2023a). The purpose of continuous monitoring is to maintain an up-to-date understanding of a bank's activities, organizational structure, and risk profile, and to identify emerging risks in a timely manner. Information obtained through continuous monitoring informs supervisory judgments, including decisions about the timing, scope, and focus of future examinations (Federal Reserve Board 2023a, Hirtle and Kovner 2022).

Supervision by the Federal Reserve is risk-focused and tailored to the size, complexity, and activities of supervised institutions. Supervisory resources are allocated based on assessments of risk and systemic importance rather than according to a fixed supervisory schedule. As a result, larger and more complex institutions are subject to more intensive supervisory engagement, both in terms of examination activity and ongoing monitoring, while smaller and less complex institutions typically receive less frequent supervisory attention (Federal Reserve Board 2023a). The intensity and composition of supervision therefore vary systematically across banks and over time.

When supervisors identify material deficiencies through examinations or continuous monitoring, they may require banks to undertake corrective actions. These actions range from informal supervisory guidance to formal enforcement actions, depending on the severity and persistence of the issues identified (Federal Reserve Board 2023c). Through this combination of examinations, continuous monitoring, and follow-up actions, Federal Reserve supervision seeks to mitigate risks at individual institutions and to support the stability of the U.S. banking system as a whole (Hirtle and Kovner 2022).

3 Data

Our data set comprises information on all the bank holding companies (BHCs) active in the U.S. and with available data in the quarterly regulatory FR Y-9C over the period from 2016Q1 to 2022Q4. We supplement these data with bank-level information from the regulatory Call Reports and confidential administrative information on supervisory hours from the Federal Reserve.

A Bank liquidity measures

Our main outcome variable is the Liquidity Coverage Ratio (LCR), a regulatory standard introduced under the Basel III framework designed to ensure that banks maintain a sufficient stock of liquid assets to survive acute short-term funding stress. It reflects the principle that banks should hold enough high-quality liquid assets (HQLA) to cover net cash outflows expected during a standardized 30-day stress scenario. The LCR is defined as:

$$LCR = \frac{\text{High-quality liquid assets}}{\text{Expected 30-day net outflows}} \tag{1}$$

The LCR constrains banks' maturity transformation by linking the composition of liabilities to the required liquidity buffer, thus internalizing the liquidity risk posed by unstable short-term funding. Its aim is to strengthen individual institutions' resilience and, by reducing the risk of fire sales and funding runs, promote overall financial stability.

To operationalize equation (1), we use Call Reports data following Hong, Huang, and Wu (2014) and Sundaresan and Xiao (2024). The Call Reports are quarterly regulatory filings submitted by U.S. commercial banks to their federal regulators (the FDIC, the Federal Reserve, and the OCC), providing detailed balance sheet and income statement data. High-quality liquid assets (numerator) are obtained combining cash and balances from depository institutions, Treasury and agency securities, and other liquid securities, weighted to reflect relative liquidity. Expected 30-day net outflows (denominator) are estimated using a liability-weighted formula, assigning regulatory-style run-off weights to different categories of liabilities, such as demand deposits (with lower weights for stable retail insured deposits), time deposits and wholesale funding (with higher run-off rates), and off-balance-sheet items like unused commitments (estimated using proxies). Both numerator and denominator components are summed using the appropriate regulatory-inspired weights, aiming to reflect the liquidity value (for assets) or risk of net outflows (for liabilities).

The LCR is computed for individual banks in the Call Reports data. We aggregate this information to the bank holding company level by forming a weighted average of the individual banks' LCRs, with weights proportional to their total assets. Table 1 shows that, on average, the LCR in our data is 0.754, close to the value of 0.822 reported by Sundaresan and Xiao (2024) for LCR banks using pre-EGRRCPA data.

B Supervisory hours

As our main measure of the intensity of supervision to which a given bank holding company is subject, we use supervisory hours from a proprietary, confidential dataset compiled by the Federal Reserve System, also used by Hirtle, Kovner, and Plosser (2020). The data track the amount of supervisory attention each bank receives over time, measured in examiner hours. These data are drawn from the Federal Reserve's internal systems used to plan and record supervisory activities; they include both on-site examinations and off-site monitoring, and capture the total number of supervisory staff hours allocated to a given bank in each quarter, offering a granular, time-varying proxy for the intensity of supervision.

The dataset covers all institutions under Federal Reserve supervision, including both state member banks and bank holding companies. Because it originates from operational planning and staffing tools used by supervisors, our measure reflects actual resource deployment rather than ex post assessments or outcomes. This makes it a uniquely detailed and direct measure of supervisory effort.

In tests described in Section 4.B, we decompose overall supervisory hours into examination hours and continuous monitoring hours. Examination hours capture the time spent by Federal Reserve supervisors conducting formal supervisory examinations. Continuous monitoring hours reflect ongoing supervisory activities outside of formal examinations. These activities primarily consist of meetings between supervisors and bank management. In preparation for such meetings, examiners review and analyze bank-generated information, including internal data, audit reports, and regulatory filings, and coordinate with other regulatory agencies. The purpose of continuous monitoring is to maintain a current understanding of a bank's activities, organizational and management changes, and associated policies and practices. Information gathered through continuous monitoring informs supervisory judgments, including whether planned examinations should be adjusted in timing, scope, or focus. The intensity of continuous monitoring varies systematically with a bank's size and complexity (Federal Reserve Board 2023a).

C Other control variables

We use the FR Y-9C Consolidated Financial Statements for Holding Companies, a regulatory report filed quarterly by U.S. bank holding companies with total consolidated assets above a specified threshold. The FR Y-9C provides detailed balance sheet and income statement data, including information on loan portfolios, securities holdings, capital ratios, and off-balance-sheet exposures. These data are collected by the Federal Reserve and are widely used to analyze the financial condition and risk profile of BHCs. We construct control variables that capture key aspects of bank characteristics, such as size (log total assets), an indicator for publicly listed BHCs, asset composition and quality (loans/assets, HHI of assets, NPL to assets), deposit market share, performance (ROA, loan growth), capital adequacy (Tier 1 capital ratio), funding structure (deposits/liabilities). These controls allow us to account for heterogeneity across banks in terms of their financial strength and business models. In addition, we use the Call Reports to determine the BHC's complexity (number of subsidiary banks under the umbrella of the BHC), %SMB above \$10bn and below \$10bn assets, and % national bank assets. These variables are defined in Appendix A. Finally, we use data from the Committee for a Responsible Federal Budget/COVID Money Tracker to construct $Fiscal\ Stimulus$, a measure of the deposits flowing into each BHC associated with the COVID-19 stimulus; we describe this variable in greater detail in Appendix D.

D Descriptives

Throughout the analysis, we focus on the subset of bank holding companies whose liquidity requirements were relaxed by the EGRRCPA and the subsequent tailoring rule, namely BHCs classified as Category IV and other banks under the 2019 tailoring rule.[5] We refer to these institutions as the treated group. Our baseline comparison group consists of all other BHCs operating during the sample period whose liquidity requirements were not relaxed at the same time.

Table 1 reports descriptive statistics for all variables used in the analysis, summarizing balance sheet characteristics, performance measures, and supervisory outcomes, as well as the composition of supervisory hours. The sample exhibits substantial heterogeneity in size, organizational complexity, and supervisory intensity, which motivates the inclusion of granular controls in the empirical analysis.

Table 2 compares treated BHCs to other BHCs along key observable dimensions over the period 2016Q1-2018Q2. Treated BHCs are significantly larger, more likely to be publicly listed, and exhibit higher deposit reliance and lower Tier-1 capital ratios than other BHCs. At the same time, the two groups are broadly comparable in terms of profitability, asset composition and quality, loan growth, and loan intensity.

Finally, while our baseline analysis compares treated BHCs to all other BHCs, 1.A shows that the main patterns are robust to alternative benchmarks, including comparisons with the top 100 largest BHCs, with Categories I–III institutions, and with propensity-score-matched BHCs. We therefore adopt the broader comparison group in the remainder of the paper to preserve transparency and statistical power.

[5]Appendix C lists the BHCs belonging to each category of the tailoring rule.

Table 1. Descriptive statistics
The table reports the mean, standard deviation, percentiles 25, 50, and 75, and number of observations of all the variables used in the analysis. The sample comprises all U.S. bank holding companies with available FR Y-9C data, over the period 2016Q1-2022Q4.

	Mean	**St. dev.**	**P25**	**P50**	**P75**	**N**
A. Balance sheet characteristics						
LCR	0.754	0.712	0.339	0.556	0.922	9,519
Size	15.606	1.565	14.424	15.294	16.323	9,519
Complexity	0.135	0.399	0.000	0.000	0.000	9,519
% SMB (>10b) assets	0.041	0.198	0.000	0.000	0.000	9,519
% SMB (≤10b) assets	0.001	0.034	0.000	0.000	0.000	9,519
% National bank assets	0.055	0.228	0.000	0.000	0.000	9,519
Public	0.626	0.484	0.000	1.000	1.000	9,519
Loans to assets	67.123	13.933	61.179	69.910	76.753	9,519
HHI of assets	1.168	16.794	0.331	0.419	0.557	9,519
Deposit market share	0.032	0.061	0.005	0.010	0.025	9,452
ROA	0.664	0.456	0.333	0.600	0.916	9,519
Loan growth	1.096	7.237	0.432	0.596	0.889	9,519
T1 capital ratio	0.136	0.063	0.112	0.124	0.144	9,490
NPL to assets	0.003	0.005	0.000	0.001	0.004	9,519
Deposits to liabilities	0.893	0.105	0.868	0.916	0.951	9,519
Fiscal stimulus	5.353	8.107	0.000	0.000	15.446	9,519
B. Supervision						
ln(Total sup. hours)	3.344	3.169	0.000	3.466	6.176	9,519
ln(Exam hours)	2.461	2.786	0.000	0.000	5.069	9,519
ln(Continuous hours)	1.764	2.310	0.000	0.000	3.497	9,519
Exam hours / Total hours	0.205	0.287	0.000	0.000	0.342	9,519
Tenure (qtrs)	30.702	16.061	17.000	30.000	48.000	7,620
FT Employees / BHCs	112.666	100.724	57.680	85.167	126.300	8,826

Table 2. Category IV and other firms compared to other BHCs
This table compares BHCs whose liquidity requirements were relaxed by the EGRRCPA and the tailoring rule (Category IV and "other firms") to all other BHCs in the sample. The table reports sample means for each group and the t-statistic from a test of equality of means. All variables are defined in Appendix A. The standard errors for the t-tests are clustered at the BHC level.

	Category IV and other firms	**Other BHCs**	**t-statistic**
	(1)	(2)	(3)
Size	18.492	14.993	24.74
Complexity	0.153	0.124	0.37
% SMB (>10b) assets	0.436	0.017	3.19
% SMB ($\leq$10b) assets	0.000	0.002	-1.24
% National bank assets	0.229	0.035	1.88
Public	1.000	0.517	21.55
Loans to assets	67.713	67.866	-0.06
HHI of assets	0.438	1.593	-1.25
Deposit market share	0.072	0.026	3.16
ROA	0.605	0.583	0.36
Loan growth	0.652	1.259	-1.32
T1 capital ratio	0.119	0.138	-4.50
NPL to assets	0.001	0.001	0.75
Deposits to liabilities	0.804	0.894	-2.77

4 Results

A Baseline: tailoring rule and liquidity risk

In the first part of the analysis, we examine whether the relaxation of liquidity regulation mandated by the 2018 EGRRCPA and the 2019 tailoring rule is associated with changes in banks' liquidity positions. We focus on bank holding companies (BHCs) classified as Category IV and other banks under the tailoring framework, whose liquidity requirements were relaxed following the passage of the EGRRCPA and the subsequent implementation of the tailoring rule.

We estimate the following specification at the BHC-quarter level:

$$\Delta LCR_{it} = \alpha + \beta_1 CatIV\&Other_i + \beta_2 Post_t + \beta_3 CatIV\&Other_i \times Post_t + \mu' x_{it} + \varepsilon_{it} \quad (2)$$

where ΔLCR_{it} denotes the quarterly change in the liquidity coverage ratio of BHC i in quarter t. CatIV&Other$i$ is an indicator equal to one for BHCs in the Category IV and other banks groups and zero otherwise, and Post$t$ is an indicator equal to one for quarters following the passage of the EGRRCPA (2018Q2). The coefficient of interest, β_3, captures the differential change in liquidity for treated BHCs relative to other BHCs after the regulatory relaxation.

A potential challenge is that the implementation of the tailoring rule closely preceded the onset of the COVID-19 pandemic and the associated fiscal and monetary interventions. The CARES Act, enacted in March 2020, injected an unprecedented amount of liquidity into the U.S. economy and was accompanied by a sharp increase in bank deposits system-wide. As shown in Appendix D, this episode is associated with pronounced spikes in deposits, personal savings, and fiscal expenditures. To account for these confounding dynamics, we include in x_{it} $Fiscal\ Stimulus$, a control that proxies for the inflow of deposits driven by the COVID-19 fiscal stimulus at the BHC level. We also include the full list of control variables used by Hirtle, Kovner, and Plosser (2020), as well as calendar quarter fixed effects.

Table 3 reports the estimates of equation (2). Across both specifications, we find that the liquidity coverage ratio of treated BHCs declines significantly relative to that of other BHCs following the tailoring rule. The estimated coefficient on the interaction term CatIV&Other $\times$ Post implies a relative decline in LCR of approximately 2 percentage points per quarter for treated institutions. Given that our post-period spans 18 quarters, this corresponds to a cumulative decline of about 36 percentage points relative to other BHCs.

Table 3. Tailoring rule and liquidity

The table reports the estimates of a regression of the quarterly change in LCR on an indicator equal to 1 for Category IV and other banks, and indicator equal to 1 for the period following the passage of the EGRRCPA in May 2018, and their interaction, along with control variables and calendard quarter fixed effects. The control variables, omitted from the table, are: size (natural logarithm of total assets), Tier 1-capital ratio, NPL/Assets, Deposits/Liabilities, Complexity (number of banks under the umbrella of the BHC), % SMB ($>$10b) assets, % SMB ($\leq$10b) assets, % National bank assets, Public indicator, Loans/Assets, Assets HHI, Deposit market share, ROA, Loan growth, indicators for CAMELS ratings of the BHC's subsidiary banks (all defined in Appendix A), and the $Fiscal\ Stimulus$ control for COVID stimulus-driven deposits (defined in Appendix D). The sample comprises all BHCs with available FR Y-9C data during the period 2016Q1-2022Q4. In both specifications the standard errors are clustered around individual BHCs.

	(1)	(2)
Category IV and other banks	-0.001	-0.012
	(0.008)	(0.010)
Category IV and other banks $\times$ Post	-0.019**	-0.019*
	(0.009)	(0.010)
Controls		✓
Calendar quarter f.e.	✓	✓
N	11,051	9,519
R^2	0.039	0.046

These magnitudes are economically meaningful and consistent with the visual evidence in Figure 1. Importantly, the estimates reflect differential changes in liquidity positions rather than level differences, suggesting that the regulatory relaxation is associated with a persistent adjustment in liquidity dynamics at treated BHCs, rather than a one-time reclassification effect.

B Supervisory hours and liquidity risk

We next study the role of supervisory attention in shaping banks' liquidity responses to the relaxation of liquidity regulation. We first document how the level and composition of supervisory hours change for BHCs affected by the tailoring rule, and then examine whether supervisory attention attenuates the decline in liquidity at treated institutions. To address potential endogeneity in supervisory intensity, we complement the baseline estimates with instrumental-variables specifications following Hirtle, Kovner, and Plosser (2020).

To examine how supervisory resources are reallocated following the tailoring rule, we estimate:

$$Hours_{it} = \alpha + \beta_1 CatIV\&Other_i + \beta_2 Post_t + \beta_3 CatIV\&Other_i \times Post_t + \gamma' x_{it} + \varepsilon_{it} \quad (3)$$

where $Hours_{it}$ measures supervisory intensity or composition for BHC i in quarter t. Specifically, we consider the log-number of total supervisory hours, the ratio of supervisory exam hours to total hours, the log-number of supervisory exam hours, and the log-number of continuous supervision hours. The indicator $CatIV\&Other$ identifies BHCs whose liquidity requirements were relaxed by the tailoring rule, and $Post_t$ denotes the post-EGRRCPA period. In some specifications, we additionally control for Category I–III BHCs and their interaction with the post indicator. All regressions include calendar-quarter fixed effects, and standard errors are clustered at the BHC level.

Table 4 reports the results. We find that total supervisory hours for Category IV and "other bank" BHCs increase modestly following the passage of the EGRRCPA, though the estimates are imprecise (panel A, columns 1-2). On the other hand, the composition of supervisory activity changes sharply. Category IV and "other bank" BHCs experience a significant increase in examination-based supervision: the ratio of supervisory exam hour to total supervisory hours increases by 12 percentage points relative to other BHCs (panel A, columns 3-4), an economically large increase relative to the average of 20 percentage points (Table 1). This is due to a combination of an increase in the number of supervisory exam hours and a reduction in the number of

Table 4. Composition of supervisory hours

The table reports the estimates of regressions that analyze the composition of supervisory hours around the passage of the EGRRCPA (May 2018). The sample includes all BHCs with available FR Y-9C data during the period 2016Q1–2022Q4. In panel A, the dependent variable is the natural logarithm of 1+ total supervisory hours (columns 1–2) or the ratio of supervisory exam hours to total hours (columns 3–4). In panel B, the dependent variable is the natural logarithm of exam hours (columns 1–2) or continuous supervision hours (columns 3–4). The regressions include an indicator for Category IV and other banks, an indicator for the post-EGRRCPA period, and their interaction. In both panels, columns 2 and 4 additionally include an indicator for Category I–III BHCs and its interaction with the post-EGRRCPA indicator. Standard errors are clustered at the BHC level.

A. Total and exam hours

	ln(Total hours)		**Exam/Total**	
	(1)	(2)	(3)	(4)
Category IV and other banks	0.552*	0.273	0.017	-0.021
	(0.328)	(0.427)	(0.036)	(0.042)
Category IV and other banks × Post	0.399*	0.393*	0.121***	0.124***
	(0.215)	(0.214)	(0.025)	(0.025)
Category I–III		-0.777		-0.145***
		(0.732)		(0.050)
Category I–III × Post		-0.108		0.054**
		(0.197)		(0.025)
Controls	✓	✓	✓	✓
Calendar quarter f.e.	✓	✓	✓	✓
N	9,519	9,519	9,519	9,519
R^2	0.414	0.415	0.081	0.083

Table 4. Composition of supervisory hours (continued)

B. Exam hours and continuous monitoring hours

	ln(Exam hours)		ln(Monitoring hours)	
	(1)	(2)	(3)	(4)
Category IV and other banks	0.824***	0.743**	1.092***	1.186***
	(0.290)	(0.365)	(0.278)	(0.375)
Category IV and other banks × Post	0.557***	0.560***	-1.665***	-1.699***
	(0.180)	(0.181)	(0.296)	(0.294)
Category I–III		-0.285		0.666
		(0.579)		(0.560)
Category I–III × Post		0.080		-0.702
		(0.166)		(0.437)
Controls	✓	✓	✓	✓
Calendar quarter f.e.	✓	✓	✓	✓
N	9,519	9,519	9,519	9,519
R^2	0.426	0.426	0.490	0.490

continuous supervision hours. These patterns are consistent with supervisory attention shifting along the intensive margin – from ongoing monitoring toward discrete examinations – rather than expanding uniformly following the regulatory relaxation.

These changes in supervisory composition raise the possibility that supervisory attention may condition how banks adjust their liquidity positions following the tailoring rule. To test this hypothesis, we extend the baseline liquidity specification (equation 2) to allow the post-EGRRCPA effect for treated BHCs to vary with supervisory intensity, interacting the treatment indicator and post period with the logarithm of supervisory hours:

$$\begin{aligned}
\Delta LCR_{it} = \alpha &+ \beta_1\, CatIV\&Other_i + \beta_2\, Post_t + \beta_3\, \log(SupHours_{it}) \\
&+ \beta_4\, CatIV\&Other_i \times Post_t + \beta_5\, CatIV\&Other_i \times \ln(SupHours_{it}) \\
&+ \beta_6\, Post_t \times \ln(SupHours_{it}) \\
&+ \beta_7\, CatIV\&Other_i \times Post_t \times \ln(SupHours_{it}) \\
&+ \mu' x_{it} + \varepsilon_{it}.
\end{aligned} \tag{4}$$

One challenge in estimating equation (4) is the potential assortative matching between supervisory hours and (liquidity) risk. It is possible that riskier banks endogenously receive more attention from the supervisor, resulting in a bias in the estimated relation between risk and supervisory hours and leading us to underestimate any beneficial impact of supervision.

To address this empirical challenge, we follow Hirtle, Kovner, and Plosser (2020) and employ an instrument for supervisory hours that builds on unique institutional features of the U.S. supervisory environment. In the U.S., supervisory activities conducted by the Federal Reserve System are organized on the level of the regional Federal Reserve Banks, which are divided into 12 districts. The district boundaries were set in 1913 (Ghizoni 2013) and have little relation to present-day economic or administrative activity.[6] Hirtle, Kovner, and Plosser (2020) argue and show evidence consistent with the notion that regional Federal Reserve Banks can face a binding constraint when allocating supervisory attention within their district, so that the largest BHCs within each district receive more supervisory hours. This means that similar banks headquartered in different districts may receive very different supervisory hours. As an illustration, M&T Bank, ranked #13 in the 2nd district (New York) in terms of its total assets, may receive fewer supervisory hours than similarly-sized Regions Financial, ranked #2 in the 6th district (Atlanta).[7] Following Hirtle, Kovner, and

[6] For instance, several districts divide individual U.S. states between them. This is the case of Missouri, divided between the 8th (St. Louis) and the 10th (Kansas City) districts; Kentucky, divided between the 8th (St. Louis) and the 4th (Cleveland) districts; Mississippi, divided between the 8th (St. Louis) and the 6th (Atlanta) districts; Tennessee, also divided between the 8th (St. Louis) and the 6th (Atlanta) districts; Wisconsin, divided between the 9th (Minneapolis) and the 7th (Chicago) districts; and West Virginia, divided between the 4th (Cleveland) and the 5th (Richmond) districts.

[7] This example is fictional and exclusively for illustrative purposes, as we are not allowed to single out individual cases in the supervisory hours data.

Plosser (2020), we define within each Fed district and calendar quarter an indicator Top equal to 1 for the top five largest BHCs in the district based on assets plus BHCs within 25% of the top five. We use Top and its interactions with Category IV and other banks and the Post indicator as instrumental variables for log-supervisory hours and their interactions interactions with Category IV and other banks and the Post indicator, in a two-stage least squares (2SLS) framework.

Table 5 reports the estimates. In column 1 we report the OLS estimates; columns 2-4 report the IV/2SLS estimates. In the latter specifications, because Top is potentially related to the BHC's size (natural logarithm of total assets), we include as controls second- and third-degree polynomials in size; intuitively, they ensure that the instrument does not capture the effect of size or some other factor that relates to size, but only the effect of the BHC's *relative* size ranking within the district. Across all specifications, greater supervisory attention is associated with a smaller decline in LCR at Category IV and other banks BHCs following the EGRRCPA. The coefficient on the triple interaction between the treatment indicator, the post-EGRRCPA period, and supervisory hours is positive and statistically significant, both in OLS and in the IV specifications. This pattern implies that, among Category IV and other banks, institutions receiving more supervisory hours experience a smaller reduction in their liquidity coverage ratios after the regulatory relaxation. The magnitude and significance of this effect are stable across alternative instrumented specifications that flexibly control for bank size, suggesting that supervisory attention plays a mitigating role in the liquidity adjustment of treated BHCs rather than merely reflecting differences in scale or observable risk characteristics.[8]

The estimates are consistent with the view that exposure to more supervisory hours mitigates the liquidity deterioration for BHCs in the "Category IV" and "Other banks" categories. Their magnitudes are also economically meaningful. To fix ideas, BHCs in these categories receive on average around 10,000 supervisory hours per year, or 2,500 hours in a given quarter (Federal Reserve Board 2019). Consider a counterfactual increase to 5,000 per quarter, approximately the

[8]Since equation (4) involves multiple endogenous regressors and instruments, we report in Table 5 the Sanderson-Windmeijer F statistics associated with each endogenous variable. These statistics are uniformly large across specifications, indicating strong first-stage relationships for supervisory hours and their interactions, even in specifications that flexibly control for bank size using higher-order polynomials.

Table 5. Supervisory hours and liquidity

The table reports the estimates of equation (4). Column 1 reports OLS estimates; columns 2-4 2SLS estimates, where the Top indicator for the set of the largest BHCs in each district and its interactions are used as instrumental variables for log-supervisory hours and their interactions interactions with Category IV and other banks and the Post indicator. The sample comprises all BHCs with available FR Y-9C data over the 2016Q1-2022Q4 period. In all specifications the standard errors are clustered around individual BHCs.

	(1)	(2)	(3)	(4)
Category IV and other banks	0.201***	0.228**	0.234**	0.255**
	(0.045)	(0.107)	(0.111)	(0.109)
Cat. IV & other × Post	-0.170***	-0.428***	-0.430***	-0.429***
	(0.060)	(0.137)	(0.134)	(0.139)
ln(Sup. hours)	-0.001	0.008*	0.008*	0.011*
	(0.001)	(0.004)	(0.005)	(0.006)
Cat. IV & other × ln(Sup. hours)	-0.025***	-0.030**	-0.031**	-0.033**
	(0.006)	(0.013)	(0.014)	(0.013)
Post × ln(Sup. hours)	0.002	-0.001	-0.001	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)
Cat. IV & other × Post × ln(Sup. hours)	0.017**	0.050***	0.050***	0.050***
	(0.007)	(0.017)	(0.017)	(0.017)
Size polynomial control of degree	1	1	2	3
Controls	✓	✓	✓	✓
Calendar quarter f.e.	✓	✓	✓	✓
N	9,519	9,519	9,519	9,519
R^2	0.046			
Kleibergen-Paap F stat		11.780	11.765	6.028
Sanderson-Windmeijer F stat:				
ln(Sup. hours)		57.212	56.356	29.523
Cat. IV & other × ln(Sup. hours)		52.365	56.334	38.701
Post × ln(Sup. hours)		330.228	319.100	296.379
Cat. IV & other × Post × ln(Sup. hours)		74.501	78.293	73.159

level received by Category I, II, and III banks. This implies an increase in log-Supervisory hours by $\ln(1+5{,}000) - \ln(1+2{,}500) = 0.693$. Using the estimates in column (4) of Table 5, the coefficient on the triple interaction implies that such an increase in supervisory attention is associated with an about $0.050 \times 0.693 \approx 3.5$ percentage points higher quarterly change in the LCR of Category IV and "Other banks" BHCs, or 4.47% relative to the average LCR of 78.30 percentage points from Table 1. Over the 18-quarter period between 2018Q3 and 2022Q4, this amounts to over 62 percentage points, about the size of the gap in LCR between BHCs in the "Category IV" and "Other banks" categories and the benchmark groups illustrated in Figure 1.A.

C Channels: Supervisory capacity constraints and tenure

We next explore potential mechanisms through which supervisory attention mitigates the increase in liquidity risk following the relaxation of regulatory requirements. We exploit heterogeneity in the institutional environment in which supervision takes place to shed light on two non–mutually exclusive channels. First, we examine whether the effectiveness of supervisory hours depends on supervisory capacity constraints at the Federal Reserve district level, measured by the availability of supervisory resources relative to the number of institutions overseen. Second, we study whether supervisory continuity matters, by distinguishing supervisory hours supplied by more versus less tenured supervisors. Together, these tests aim to clarify how organizational constraints and human capital shape the transmission of supervisory attention into effective risk mitigation.

We begin by examining whether the effectiveness of supervisory attention depends on supervisory capacity at the Federal Reserve district level. Intuitively, supervisory hours may translate into less effective oversight when supervisory resources are stretched thin, limiting supervisors' ability to follow up on identified issues, escalate concerns, or impose corrective actions. To capture this dimension, we construct a measure of district-level supervisory capacity based on the number of full-time equivalent (FTE) supervisory employees relative to the number of bank holding companies (BHCs) supervised in a given district and quarter.[9] Districts with higher values of this ratio

[9]The supervisory capacity variable is defined in detail in Appendix A.

have more supervisory resources available per institution. We then classify districts into high-capacity and low-capacity groups based on whether their supervisory capacity lies above or below the median in a given quarter.

We then estimate regressions similar to equation (4), separately for high- and low-capacity districts. In high-capacity districts, supervisory attention is associated with an attenuation of the LCR deterioration experienced by deregulated banks following the EGRRCPA: the coefficient on the triple interaction term Category IV & Other banks $\times$ Post $\times$ ln(Supervisory hours) is positive, statistically different from zero, and economically large. In contrast, in low-capacity districts, the corresponding interaction term is small in magnitude and statistically indistinguishable from zero. This pattern holds across both the OLS and instrumental variables specifications. These results suggest that supervisory hours are more effective in constraining liquidity risk when they are deployed in an environment with sufficient supervisory resources, consistent with capacity constraints limiting the transmission of supervisory attention into effective oversight.

We next examine whether the effectiveness of supervisory attention varies with supervisory tenure, measured as the length of time a supervisor has been active within the Federal Reserve System. Supervisors with longer tenure may be better positioned to translate supervisory attention into effective oversight, for instance because they have greater familiarity with supervisory procedures, regulatory expectations, and the institutions they oversee, or because they have previously observed episodes of financial stress. This conjecture echoes a broader literature documenting how past exposure to adverse events can shape subsequent decision-making (e.g., Malmendier and Nagel 2011), although our focus remains on tenure as an institutional characteristic rather than on individual beliefs or preferences.

To capture this dimension, we construct a measure of supervisory tenure based on the primary supervisor assigned to each bank holding company, defined as the supervisor who records the largest share of supervisory hours for that institution. We measure tenure as the number of quarters the primary supervisor has been active in the supervisory data as of 2018Q1, prior to the implementation of the EGRRCPA. We then classify banks into long-tenure and short-tenure groups

Table 6. Effect of Supervision on Bank Liquidity: By District Capacity
The table reports the estimates of regressions similar to Table 5, splitting the sample based on the Fed district's supervisory capacity (above/below the median). Supervisory capacity is proxied by the ratio of full-time supervisory employees in the district to the number of BHCs under the district's supervision.

	OLS		IV	
Capacity:	**High**	**Low**	**High**	**Low**
	(1)	(2)	(3)	(4)
Cat. IV & other	0.311***	0.127	0.313	0.250
	(0.099)	(0.165)	(0.237)	(0.499)
Cat. IV & other × Post	-0.292**	0.037	-0.688**	0.219
	(0.127)	(0.188)	(0.272)	(0.616)
ln(Sup. hours)	-0.001	-0.001	0.011	0.001
	(0.002)	(0.001)	(0.008)	(0.006)
Cat. IV & other × ln(Sup. hours)	-0.038***	-0.018	-0.038	-0.034
	(0.013)	(0.020)	(0.030)	(0.059)
Post × ln(Sup. hours)	0.000	0.004*	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Cat. IV & other × Post × ln(Sup. hours)	0.034**	-0.009	0.081**	-0.029
	(0.015)	(0.022)	(0.033)	(0.074)
Controls	✓	✓	✓	✓
Calendar quarter f.e.	✓	✓	✓	✓
N	3,551	5,275	3,551	5,275
R^2	0.044	0.058		
Kleibergen-Paap F stat				
Sanderson-Windmeijer F stat:				
ln(Sup. hours)			7.458	15.267
Cat. IV & other × ln(Sup. hours)			33.631	106.036
Post × ln(Sup. hours)			52.378	50.412
Cat. IV & other × Post × ln(Sup. hours)			195.056	535.988

depending on whether their primary supervisor's tenure lies above or below the sample median.

Using this split, we regressions similar to equation (4), separately for banks supervised by long- and short-tenure supervisors. The results are reported in Table 7. For banks whose primary supervisor has longer tenure, supervisory hours are associated with a stronger attenuation of the post-EGRRCPA liquidity deterioration: the coefficient on the triple interaction term Category IV & Other banks $\times$ Post $\times$ ln(Supervisory hours) is positive and statistically significant in the OLS specification. In contrast, for banks supervised by lower-tenure supervisors, the corresponding effect is smaller in magnitude and statistically indistinguishable from zero. The instrumental-variables estimates point in the same direction but are less precisely estimated. Overall, these results provide suggestive evidence that supervisory tenure shapes the effectiveness of supervisory attention, although the estimates are noisier than for the capacity channel.

D Technology, AI, and supervision

Our findings highlight the importance of supervisory attention and supervisory capacity in mitigating the adverse liquidity effects of regulatory relaxation. At the same time, they raise a natural question about how to reconcile the apparent benefits of supervision with the recent announcements of non-trivial staff reductions at the Federal Reserve and other supervisory authorities. One possible interpretation is that technological change, often referred to as SupTech, may partially offset reductions in headcount by increasing the productivity of supervisors. Recent work documents that digital supervisory tools can strengthen compliance and discipline bank behavior (Degryse, Huylebroek, and Van Doornik 2025) and that successful SupTech adoption depends critically on organizational readiness and task suitability (Gambacorta, Lauridsen, Kiuhan-Vásquez, and Prenio 2025). These developments suggest that supervision need not scale one-for-one with staff numbers if technology meaningfully augments supervisors' effectiveness.

A complementary perspective is to interpret supervisory hours as an input that reflects, in part, time spent on document-intensive tasks such as reviewing regulatory filings, drafting supervisory communications, and synthesizing complex information. Evidence from other professional set-

Table 7. Effect of Supervision on Bank Liquidity: By Supervisor Tenure
The table reports the estimates of regressions similar to Table 5, splitting the sample based on the length of the tenure of the BHC's primary supervisor, measured as the number of quarters the primary supervisor has been active in the supervisory data as of 2018Q1, prior to the implementation of the EGRRCPA.

	OLS		IV	
Tenure:	**Long**	**Short**	**Long**	**Short**
	(1)	(2)	(3)	(4)
Cat. IV & other	0.020	0.246***	-0.026	0.182
	(0.174)	(0.093)	(0.257)	(0.354)
Cat. IV & other × Post	-0.396***	-0.086	-0.345	0.109
	(0.124)	(0.094)	(0.211)	(0.411)
ln(Sup. hours)	-0.002	-0.001	0.012**	0.005
	(0.002)	(0.002)	(0.005)	(0.012)
Cat. IV & other × ln(Sup. hours)	-0.001	-0.029**	0.005	-0.024
	(0.021)	(0.011)	(0.032)	(0.043)
Post × ln(Sup. hours)	0.002	0.004	0.005	-0.003
	(0.003)	(0.003)	(0.004)	(0.006)
Cat. IV & other × Post × ln(Sup. hours)	0.045***	0.006	0.036	-0.014
	(0.016)	(0.011)	(0.027)	(0.050)
Controls	✓	✓	✓	✓
Calendar quarter f.e.	✓	✓	✓	✓
N	3,793	3,827	3,793	3,827
R^2	0.064	0.048		
Kleibergen-Paap F stat			8.667	5.103
Sanderson-Windmeijer F stat:				
ln(Sup. hours)			49.667	23.559
Cat. IV & other × ln(Sup. hours)			62.305	22.350
Post × ln(Sup. hours)			233.960	197.137
Cat. IV & other × Post × ln(Sup. hours)			72.096	21.792

tings indicates that generative AI tools can substantially increase productivity in comparable activities, reducing time spent while maintaining or improving output quality. Calibrating conservatively across existing experimental estimates implies that AI assistance could raise effective output per hour by roughly 20-30% for such tasks (Noy and Zhang 2023, Peng, Kalliamvakou, Cihon, and Demirer 2023). While these technologies are unlikely to substitute for supervisory judgment, on-site examinations, or escalation decisions, they may increase effective supervisory capacity precisely along the margin captured by our supervisory-hours measure. Interpreted in this light, our results are consistent with a view in which technological advances, potentially combined with AI, can help preserve the stabilizing role of supervision even in an environment of tighter staffing constraints. Under this interpretation, technological tools such as SupTech and AI can be interpreted as shifting supervisory environments from lower- to higher-capacity settings, thereby enhancing the effectiveness of supervisory hours along the margin documented in Table 6.

5 Conclusion

We study the role of supervisory attention in shaping banks' liquidity risk following regulatory relaxation. Focusing on the implementation of the Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA), we ask whether, and under what conditions, bank supervision can mitigate the deterioration in liquidity risk experienced by deregulated banks. To address this question, we combine detailed data on supervisory hours from the Federal Reserve with bank-level balance-sheet information, exploiting cross-district and cross-bank variation in supervisory intensity around the reform.

Our main findings show that deregulated banks experience a significant decline in liquidity after the EGRRCPA, but that this deterioration is meaningfully attenuated when banks receive greater supervisory attention. These effects are economically large and robust across specifications, including instrumental-variables estimates that leverage exogenous variation in supervisory hours driven by district-level assignment and workload. Importantly, the results suggest that supervision operates as a stabilizing force even when formal regulatory requirements are relaxed, highlighting supervision as a distinct and active policy tool rather than a passive complement to regulation.

We further shed light on the mechanisms through which supervision matters. The mitigating effect of supervisory attention is concentrated in Federal Reserve districts with greater supervisory capacity, measured by supervisory resources relative to the number of institutions overseen, and is weaker or absent where capacity constraints are more binding. We also find suggestive evidence that supervisory tenure shapes effectiveness, with stronger effects when banks are overseen by longer-tenured supervisors. Taken together, these results point to the importance of organizational and human constraints in the transmission of supervisory attention into effective risk mitigation. More broadly, they underscore that the effectiveness of supervision depends not only on the quantity of supervisory effort, but also on the institutional environment in which it is deployed.

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Appendix to “Mitigating the risks of deregulation: The role of supervisory attention”

by Elena Carletti, Filippo De Marco, Alberto Manconi, and Isabella Wolfskeil

A Variables description

A.1 Variables based on the FR Y-9C and Call Report data

LCR Liquidity Coverage Ratio, computed as described in Appendix B.

Size Natural logarithm of total assets (FR Y-9C data item BHCK2170).

Loans to assets Ratio of loans (FR Y-9C data item BHCK2122) to total assets.

Loan growth Growth rate of loans.

ROA Ratio of income before extraordinary items (FR Y-9C data item BHCK4300) to total assets.

T1 capital ratio Ratio of Tier 1 capital (FR Y-9C data item BHCK8274) to risk-weighted assets (FR Y-9C data item BHCKA223).

NPL to assets Ratio of non-performing loans (sum of FR Y-9C data items BHCKA223 and BH-CAA223 to total assets).

Deposits to liabilities Ratio of deposits (sum of FR Y-9C data items BHDM6631, BHDM6636, BHFN6631, and BHFN6636) to total liabilities (FR Y-9C data item BHCK3300).

HHI of assets Defined following Kovner, Vickery, and Zhou (2014), as the sum of the squares of the shares of loans to individuals for household, family, and other personal expenditures, residential real estate loans, commercial real estate loans, C&I loans, investment securities, and trading assets in total BHC assets. Instead of loans to individuals for household, family, and other personal expenditure (FR Y-9C data item BHDM1975), Kovner, Vickery, and Zhou (2014) use credit card loans, defined as FR Y-9C data item BHCKB538, but this item is not available for most of our sample period. Residential real estate loans are defined as the sum of FR Y-9C data items BHDM1797, BHDM5367, and BHDM5368. Commercial real estate loans are defined as total loans (FR Y-9C data item BHCK1410) minus residential real estate loans (BHDM1797 plus BHDM5367 plus BHDM5368) minus FR Y-9C data items BHCKF160 and BHDM1420 (Kovner, Vickery, and Zhou (2014) use data items BHCKf158, BHCKF159, and BHCKF161; but these items are missing for most of our sample). C&I loans are defined as FR Y-9C data item BHDM1766. Investment securities are defined as FR Y-9C data items BHCK1754 plus BHCK1773. Trading assets are defined as FR Y-9C data item BHCK3545.

Complexity Number of banks with data in the Call Reports under the umbrella of the BHC.

% SMB (≤$10bn) assets / % SMB (>$10bn) assets % of SMBs (entity type equal to "SMB") with total assets below/above $10bn in the total assets of the BHC.

% National bank assets % of national banks (entity type equal to "NAT") in the total assets of the BHC.

A.2 Confidential data on supervisory hours

ln(Total Sup. Hours) Natural log of total supervisory hours associated with a bank holding company in a given quarter. Hours are aggregated from the ROAM data.

ln(Exam Hours) Natural log of supervisory hours where the category of work is associated with an examination. This is a subset of total supervisory hours.

ln(Continuous Hours) Natural log of supervisory hours where the category of work is associated with ongoing supervision or continuous monitoring activities. This is a subset of total supervisory hours and captures non-examination supervisory attention.

Exam/Total Ratio of examination hours to total supervisory hours in a given bank-quarter. This measure captures the composition of supervisory attention between periodic examinations and ongoing monitoring. A version that fills in zeros for bank-quarters with no recorded hours is also used.

Rate 2–5 Indicator variables for CAMELS composite ratings of 2, 3, 4, or 5 (least sound), where a rating of 1 is the omitted category.

Tenure (qtrs) Tenure of the primary supervisor assigned to a bank as of 2018Q1, measured in quarters. The primary supervisor is identified as the employee who recorded the most hours for a given bank in each quarter. Tenure is calculated using the anonymized employee identifier in the ROAM hours data by identifying the first quarter the supervisor appears in the data and computing the number of quarters elapsed between that first appearance and 2018Q1. This fixed-point measure captures supervisory experience at the onset of the EGRRCPA implementation.

High/Low Tenure An indicator for whether a bank's primary supervisor has above-median tenure as of 2018Q1. Banks are classified as high tenure if their primary supervisor's tenure exceeds the sample median, and low tenure otherwise.

FT Empl/BHCs Full-time equivalent (FTE) supervisory employees per BHC in a Federal Reserve district, measuring district-level supervisory capacity. FTE is calculated from the ROAM hours data by summing total hours worked by all employees in a district-quarter and dividing by 520 (corresponding to a 40-hour work week over a 13-week quarter). This is then divided by the number of unique BHCs supervised in that district-quarter. Districts with higher values have more supervisory resources available per institution.

High/Low Capacity District An indicator for whether a bank's Federal Reserve district has above-median supervisory capacity. Districts are ranked each quarter by FTE per BHC, and banks in districts ranked 7–12 (top half) are classified as high capacity, while banks in districts ranked 1–6 (bottom half) are classified as low capacity.

B Computing the LCR

This Appendix describes the construction of a regulatory-style Liquidity Coverage Ratio (LCR) for U.S. bank holding companies (BHCs) using publicly available data. Our starting point is the methodology developed by Hong, Huang, and Wu (2014), which maps Basel III liquidity standards into Call Report information and has been adopted in subsequent work, including Passmore and Temesvary (2022), Patel, Sorokina, and Thornton (2022), and Sundaresan and Xiao (2024). A central challenge in implementing the LCR outside the supervisory environment is that publicly available balance-sheet data lack the granularity banks use internally when computing regulatory LCRs, particularly for modeling cash outflows under stress. Consistent with the existing literature, we therefore approximate Basel III definitions using observable balance-sheet items, while introducing additional heterogeneity across BHCs when more detailed regulatory filings allow us to do so. We proceed by first describing the benchmark approach and its underlying assumptions, then detailing our construction of high-quality liquid assets and net cash outflows, and finally validating the resulting LCR against banks' disclosed measures.

Our benchmark for constructing the LCR is the approach of Hong, Huang, and Wu (2014), who compute a Basel III-consistent LCR for U.S. banks using Call Report data. Their methodology is based on the original Basel III liquidity standards issued in 2010 and the subsequent revisions finalized in 2013 and 2014, and it provides a transparent mapping from regulatory definitions to publicly observable balance-sheet items. Because Call Reports do not allow for a fully granular implementation of the regulatory rules, Hong, Huang, and Wu (2014) introduce a set of simplifying assumptions (most notably regarding the composition and stability of funding sources) and assess robustness by considering alternative optimistic and pessimistic scenarios.

We adopt this framework as our point of departure and retain its core structure, while updating several assumptions to better reflect heterogeneity across bank holding companies and changes in available regulatory disclosures over time. In particular, where more detailed regulatory filings permit, we replace fixed or sample-wide assumptions with bank-specific measures, while maintaining consistency with the Basel III definitions and the spirit of the original approach.

High-quality liquid assets (HQLA). The numerator of the Liquidity Coverage Ratio is the stock of high-quality liquid assets (HQLA). We construct HQLA following the Basel III definitions and the implementation in Ihrig, Kim, Vojtech, and Gretchen C (2019), using publicly available Call Report data. Under Basel III, HQLA are classified into three categories, Level 1, Level 2A, and Level 2B, based on their liquidity and credit risk characteristics, with category-specific haircuts and aggregate caps.

Level 1 assets are the most liquid and are not subject to haircuts. They include cash, reserve balances held at the central bank, and securities issued or guaranteed by the U.S. government. Level 2A assets include certain securities issued or guaranteed by U.S. government-sponsored enterprises (GSEs) and are subject to a 15% haircut. Level 2B assets consist primarily of certain corporate debt securities, which are subject to a 50% haircut and, together with Level 2A assets, are subject to an aggregate cap of 40% of total HQLA. Because Level 2B assets account for only a marginal share of HQLA holdings in our sample, we exclude them from our analysis.

Consistent with these definitions, we identify the following assets as Level 1 HQLA: (i) excess reserves, (ii) U.S. Treasury securities, and (iii) Government National Mortgage Association (Ginnie Mae) mortgage-backed securities and other non-GSE agency debt. We classify as Level 2A

HQLA: (i) GSE debt, (ii) GSE mortgage-backed securities, and (iii) GSE commercial mortgage-backed securities. All asset categories are identified using specific line items in the Call Report, and the corresponding regulatory haircuts and caps are applied in constructing total eligible HQLA.

Net cash outflows. The denominator of the Liquidity Coverage Ratio is the total net cash outflows over a 30-day stress period. We construct this component following the framework of Hong, Huang, and Wu (2014), which maps Basel III runoff and inflow assumptions into publicly available balance-sheet data. Under this approach, net cash outflows are computed as expected cash outflows net of expected cash inflows, where outflows depend on the composition and stability of funding sources and inflows are subject to regulatory caps.

As in Hong, Huang, and Wu (2014), the main challenge in implementing this framework with public data is the limited observability of funding stability and counterparty characteristics that enter the Basel III runoff rates. Their baseline implementation therefore relies on simplifying assumptions regarding the composition of wholesale versus retail funding, and explores alternative optimistic and pessimistic scenarios to assess sensitivity. We adopt their baseline structure but introduce several modifications to allow for heterogeneity across bank holding companies and over time, while remaining consistent with the regulatory definitions.

Our first modification concerns the composition of retail and wholesale funding. Rather than assuming a fixed or scenario-dependent share of wholesale funding, we exploit information from the FR Y-15 Systemic Risk Report, which provides a detailed breakdown of funding sources for U.S. bank holding companies with combined U.S. assets of at least $100 billion. Beginning in 2020, these filings are available at a quarterly frequency and allow us to measure each BHC's share of retail funding directly.[10] For BHCs that do not file the FR Y-15, and for quarters prior to 2020, we impute the retail funding share using the average across banks in our sample, which is approximately 60%.[11]

A second modification concerns outstanding lines of credit and other off-balance-sheet commitments. Consistent with the Basel III liquidity coverage framework and the U.S. LCR Final Rule, we assume an average drawdown rate of 20 percent on these commitments when computing expected cash outflows.[12]

All other components of net cash outflows follow the baseline implementation of Hong, Huang, and Wu (2014).

Benchmark comparison and validation. Having constructed the numerator and denominator of the LCR, we next compare the resulting measure with the benchmark implementation of Hong, Huang, and Wu (2014) to assess how our refinements affect both the level and the dynamics of the LCR over time. Figure B.1 compares the asset-weighted average LCR implied by our approach with the LCR computed using the baseline methodology of Hong, Huang, and Wu (2014), for bank holding companies in regulatory Categories I-III and Category IV and other banks under the 2019

[10]Specifically, Schedule F, variable 2 reports total retail funding. We use this value to compute the share of retail funding in total deposits reported in the FR Y-9C.

[11]Hong, Huang, and Wu (2014) assume a wholesale funding share of 50% in their baseline scenario, 20% in their optimistic scenario, and 80% in their pessimistic scenario.

[12]Details of the regulatory treatment of cash outflows and inflows are available in the U.S. LCR Final Rule, Federal Register, https://www.ecfr.gov/current/title-12/chapter-II/subchapter-A/part-249/subpart-D/section-249.30.

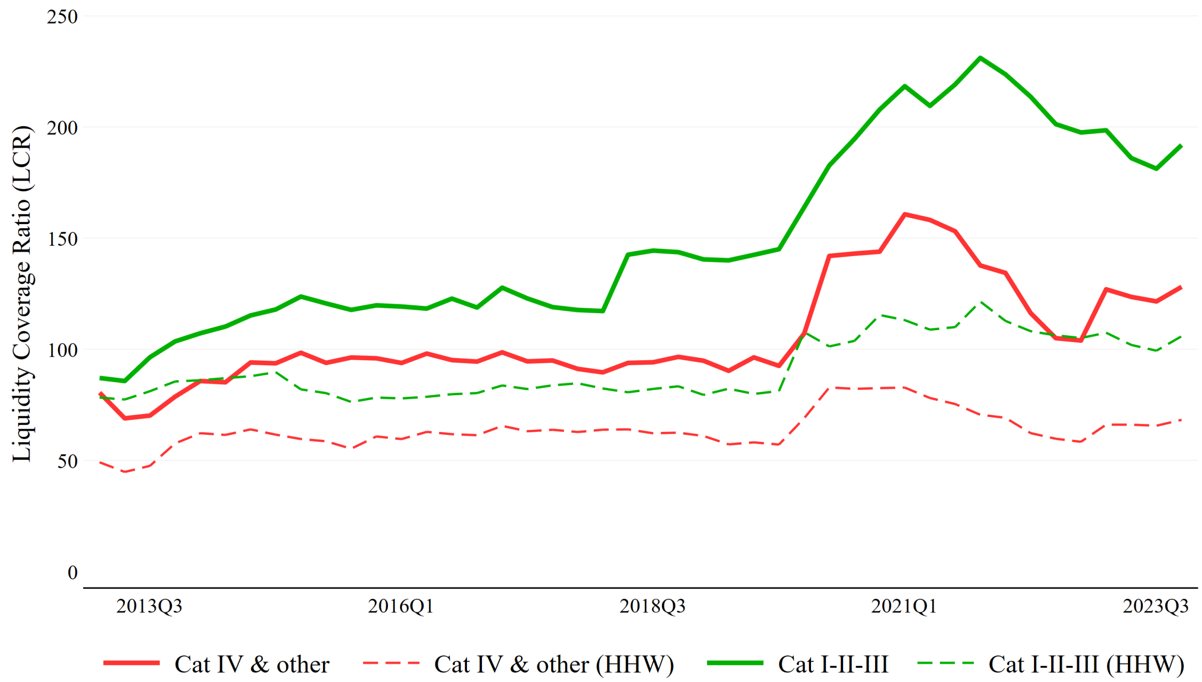

Figure B.1. LCR computation

The figure compares the LCR calculated using the Hong, Huang, and Wu (2014) method and our computation. It shows the total asset weighted averages BHC LCRs for the period 2013Q1-2023Q4, for categories I-II-III and IV-other from the 2019 tailoring rule.

tailoring rule, over the period 2013Q1-2023Q4. Across both groups, the LCR constructed using our approach is generally higher than that obtained under the benchmark method.

The difference in levels primarily reflects our use of more granular information on funding composition, which leads to lower estimated net cash outflows for some institutions relative to the benchmark assumptions. Importantly, despite these level differences, the two series exhibit very similar time-series dynamics, suggesting that our refinements do not materially alter the cyclical behavior of the LCR.

A further and quantitatively important source of divergence between our BHC-level LCR and the benchmark measure relates to the treatment of transferability restrictions under the U.S. LCR Final Rule. When reporting their consolidated LCR, U.S. bank holding companies are subject to restrictions that limit the amount of high-quality liquid assets (HQLA) that can be transferred from their banking subsidiaries to the parent entity.[13] In particular, the amount of eligible HQLA held at the subsidiary level that can be recognized at the parent level is capped by the subsidiaries' net cash outflows. As a result, the consolidated LCR of the parent BHC may be lower than what would be obtained by mechanically aggregating subsidiary balance sheets.

We explicitly account for these transferability restrictions when constructing the BHC-level LCR. Specifically, we cap the contribution of subsidiaries' eligible HQLA at their respective net cash outflows, and add parent-level HQLA holdings that are not subject to such constraints, including Treasury securities and excess reserves held directly by the parent.[14]

Figure B.2 shows that, once these transferability restrictions are incorporated, the LCR of Category I-III banks computed under our approach closely tracks both the level and the dynamics of the average LCR disclosed by banks in our sample. By contrast, the benchmark measure of Hong, Huang, and Wu (2014), which is based on a mechanical consolidation of subsidiary balance sheets, frequently yields BHC-level LCRs below 100 percent. In such cases, transferability restrictions are effectively non-binding, making the benchmark measure less comparable to the regulatory LCR reported by large U.S. bank holding companies.

We validate our constructed LCR by comparing it with LCRs publicly disclosed by large U.S. bank holding companies. Figure B.2 shows that, once transferability restrictions are incorporated, our measure closely matches both the level and the time-series dynamics of the disclosed LCR for banks in our sample.

Table B.1 reports the correlation between disclosed LCRs and LCRs computed under alternative approaches. Our preferred specification exhibits the highest correlation with the disclosed data, while implementations that omit eligibility criteria or transferability restrictions display substantially lower correlations.

[13] See the U.S. LCR Final Rule, Federal Register, https://www.federalregister.gov/documents/2014/10/10/2014-22520/liquidity-coverage-ratio-liquidity-risk-measurement-standards.

[14] To the capped sum of subsidiary-level eligible HQLA, we add Treasury securities held by the parent (FR Y-9LP Schedule PC, item 2.a.) and intragroup deposits held by the parent, which we assume to be fully backed by reserve balances. This amount is calculated as the maximum of intragroup deposits reported in FR Y-9LP Schedule PC, item 1.a.

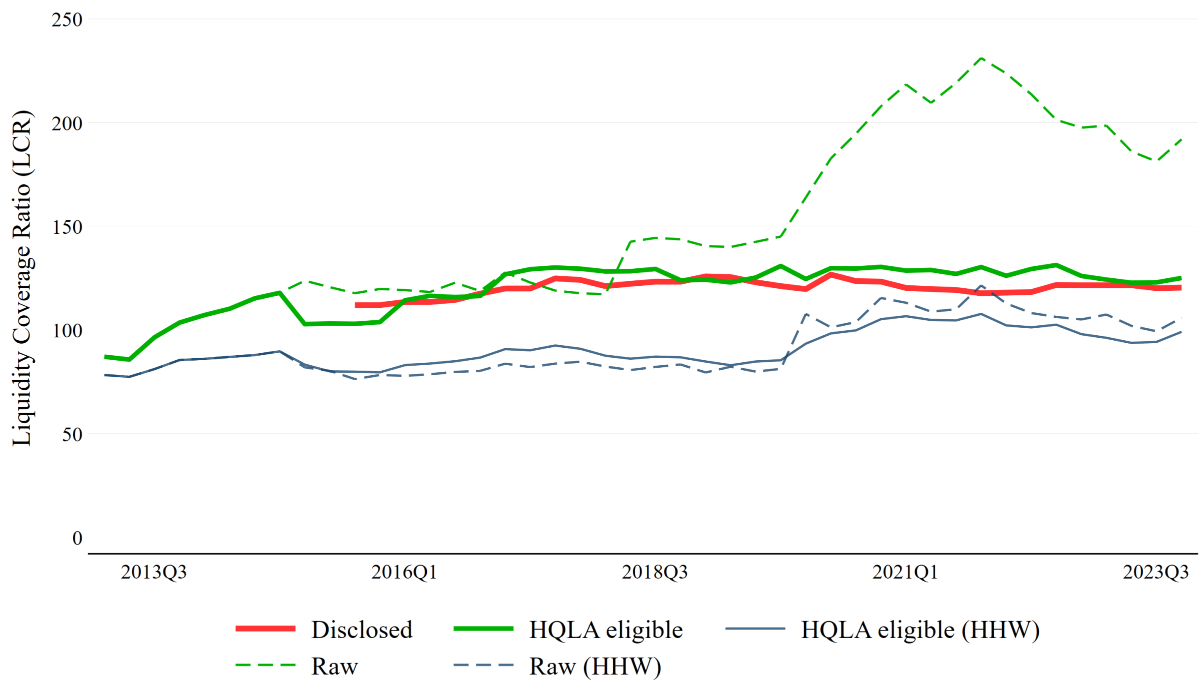

Figure B.2. Computed LCR and disclosed LCR
The figure plots the LCR disclosed by category I-II-III banks, comparing it to the LCR computed based on our approach, raw and accounting for the HQLA eligibility cap, and to the LCR computed based on the Hong, Huang, and Wu (2014) approach, raw and accounting for the HQLA eligibility cap.

Table B.1. Correlation between disclosed and computed LCR.
The table reports the correlation between the LCR disclosed by banks in our sample and the LCR computed under the different approaches described in this Appendix.

Our approach		Hong, Huang, and Wu (2014)	
HQLA eligible	Raw	HQLA eligible	Raw
0.768	0.171	0.226	0.145

C Lists of bank holding companies in the 2019 tailoring rule

Category I Bank holding companies in this category as the U.S. GSIBs: Bank of America, Bank of New York Mellon, Citigroup, Goldman Sachs, JPMorgan Chase, Morgan Stanley, State Street, Wells Fargo

Category II Bank holding companies in this category have over $700bn total assets or over $75bn in cross-jurisdictional activity: Northern Trust

Category III Bank holding companies in this category have over $250bn total assets or over $750bn in NBA, wSTWF, or off-balance sheet exposure: Capital One, Charles Schwab, PNC Financial, and U.S. Bancorp

Category IV Bank holding companies in this category have total assets between $100bn and $250bn: Ally Financial, American Express, BB&T Corp., Citizens Financial, Discover, Fifth Third, Huntington, KeyCorp, M&T Bank, Regions Financial, SunTrust Inc., Synchrony Financial

Other firms Bank holding companies in this category have total assets between $50bn and $100bn: Comerica Inc., CIT Group Inc., E*TRADE Financial, NY Community Bancorp, Silicon Valley Bank

D 2020 CARES Act and *Fiscal Stimulus* control variable

On 27 March 2020 the CARES Act launched the largest stimulus package in U.S. history, worth \$2.5Tr, or about 12% of U.S. GDP. Most of the stimulus materialized over the year 2020 and in early 2021. In comparison, the stimulus launched in the wake of the Great Recession was smaller at \$1.8Tr, and more importantly it was spent more gradually. As illustrated in Figure D.1, we observe a sharp spike in deposits, the personal savings rate, and fiscal expenditures. The result is a pronounced increase in liquidity in the U.S. banking system.

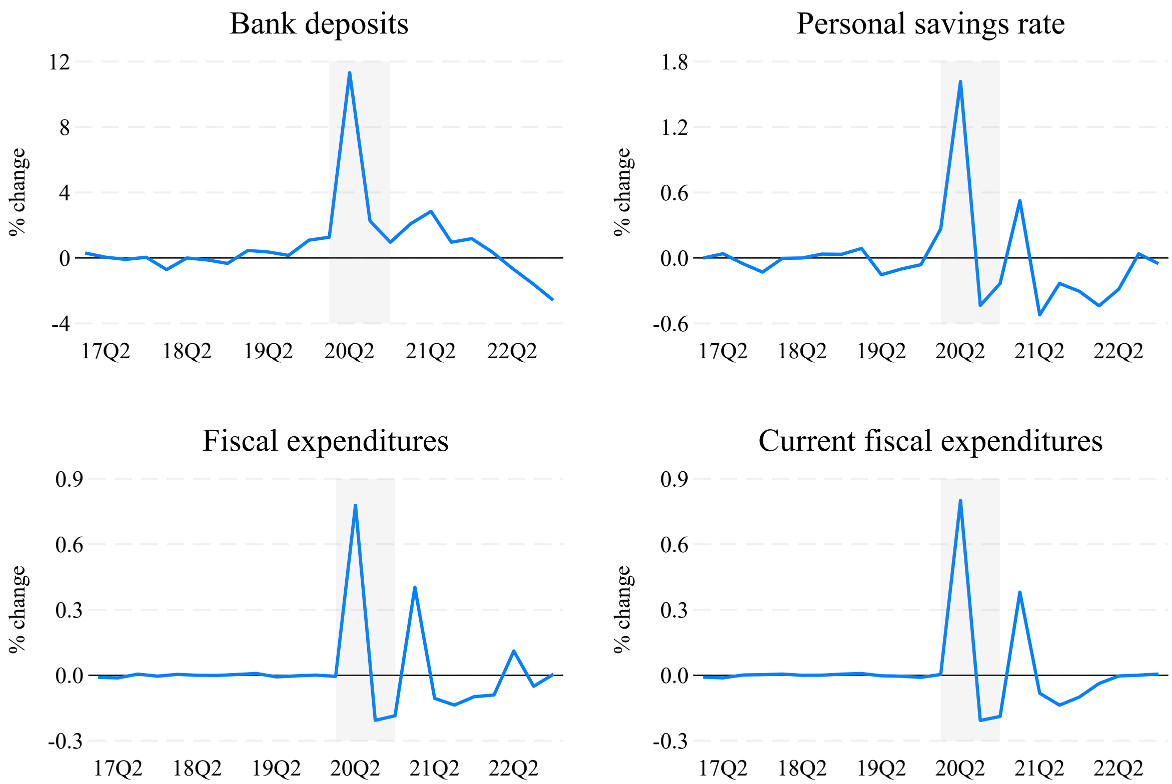

Figure D.1. COVID stimulus package
The figure illustrates the effects of the COVID stimulus package associated with the CARES Act. In all graphs, the area shaded in gray corresponds to the calendar year 2020, during which the stimulus materialized.

To control for the impact of the COVID stimulus package on bank liquidity, we include in our tests a control variable *Fiscal Stimulus*, reflecting the flow of liquidity into bank deposits associated with the COVID stimulus. The variable is constructed from input data from the COVID Money Tracker (CMT, https://www.covidmoneytracker.org/), which tracks federal spending, tax cuts, loans, grants, and subsidies authorized and disbursed in response to the pandemic. We remove duplicates using the program hierarchy to avoid double-counting and restrict the attention to non-zero disbursements and a valid single U.S. state or territory as the recipient.

Next, each program (and respective amount) is classified as fiscal or monetary policy based on the CMT taxonomy (Level 1 aggregation). We label a program as Fiscal if its origin is indicated as "Legislative" or "Administrative". We further map the result into a small set of economically meaningful categories corresponding to loans and different types of deposits: Consumer ("Direct Payments," "Income Support," "Trump Administration," "Tax Policy," "Other Spending"), State ("State & Local Funding," "State & Local'), and Wholesale ("Health programs," "Health spending").[15] The result is a balanced state, quarter, and spending category panel.

Finally, these state-level spending measures are mapped to bank holding companies using pre-pandemic branch deposit data from the FDIC. For each bank, we compute the deposit shares at the state level based on the distribution of branch deposits. State-level COVID spending is then allocated to banks proportionally to these deposit shares. The $Fiscal\ Stimulus$ variable is defined as the sum of the Consumer, State, and Wholesale components.

[15] A separate category consists of fiscal stimulus components affecting corporations, reported in the CMT as "Business support" and "Loan programs."